

Practical Leverage Score-Based Sampling for Low-Rank Tensor Decompositions

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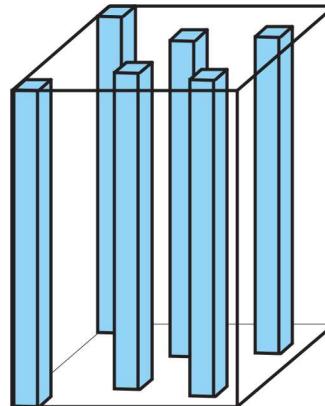
Stanford University

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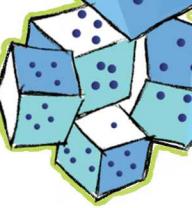
Joint work with:

Tamara G. Kolda

Sandia National Laboratories

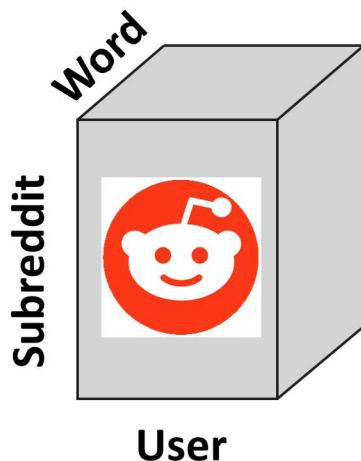


Tamara G. Kolda



Example Sparse Multiway Data: Reddit

- Reddit is an American social news aggregator, web content rating, and discussion website
 - A “ subreddit” is a discussion forum on a particular topic
- Tensor obtained from frost.io (<http://frostd.io/tensors/reddit-2015/>)
 - Build from reddit comments posted in the year 2015
 - Users and words with less than 5 entries have been removed



Reddit Tensor

8 million users

4.7 billion non-zeros ($10^{-8}\%$)

200 thousand subreddits

106 gigabytes

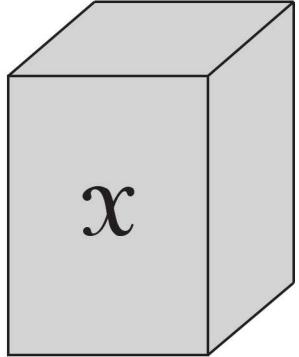
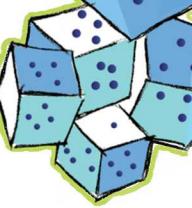
8 million words

$$x(i, j, k) = \log (1 + \text{the number of times user } i \text{ used word } j \text{ in subreddit } k)$$

Used a rank $r = 25$ decomposition

Smith et al (2017). “FROSTT: The Formidable Open Repository of Sparse Tensors and Tools”

CP Decomposition into Rank-1 Components

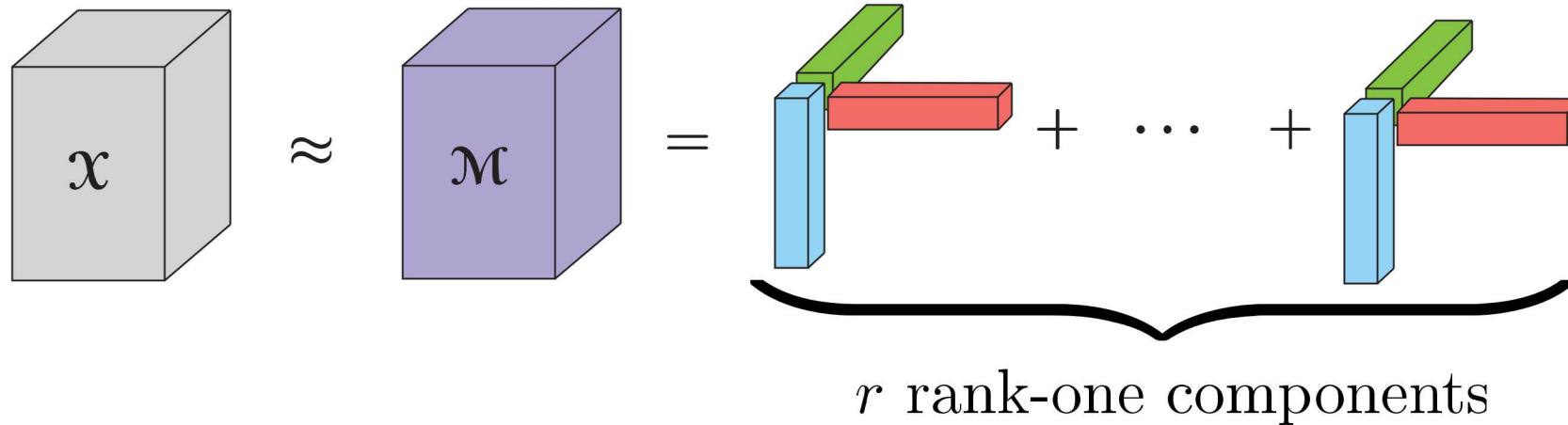


Tensor Properties

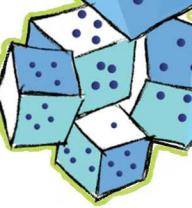
Order: 3 | \mathcal{X} is a 3-way tensor.

Length of each dimension: n_1, n_2, n_3

\mathcal{X} is $n_1 \times n_2 \times n_3$



Rank r
Decomposition



Tensor Decomposition Identifies Factors

Multi-Index Notation

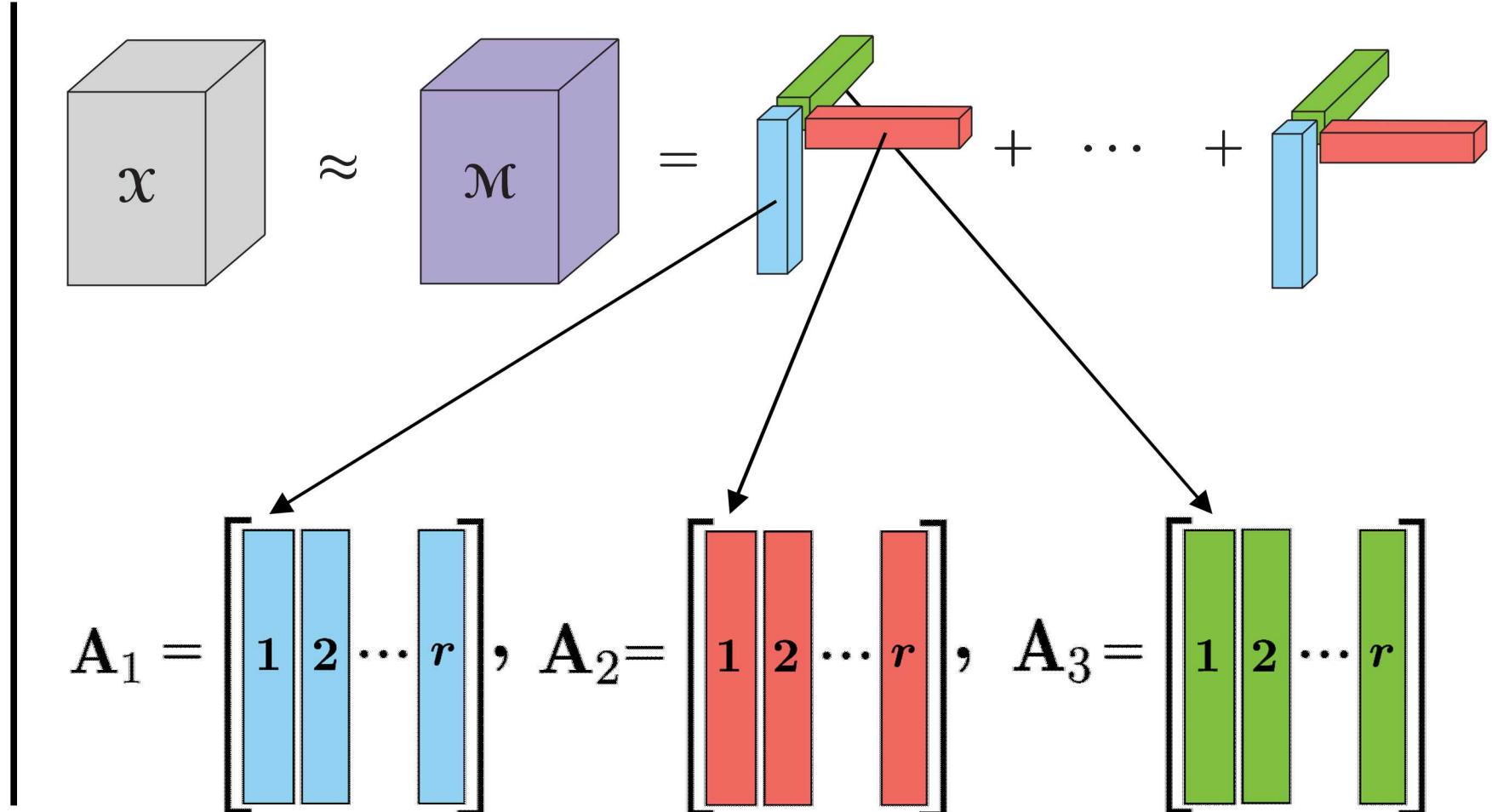
$$x_i \equiv \mathcal{X}(i_1, i_2, i_3)$$

Ω : Set of all multi-indices

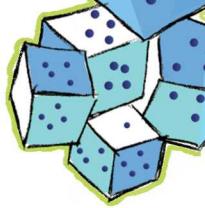
CP Decomposition

$$x_i \approx$$

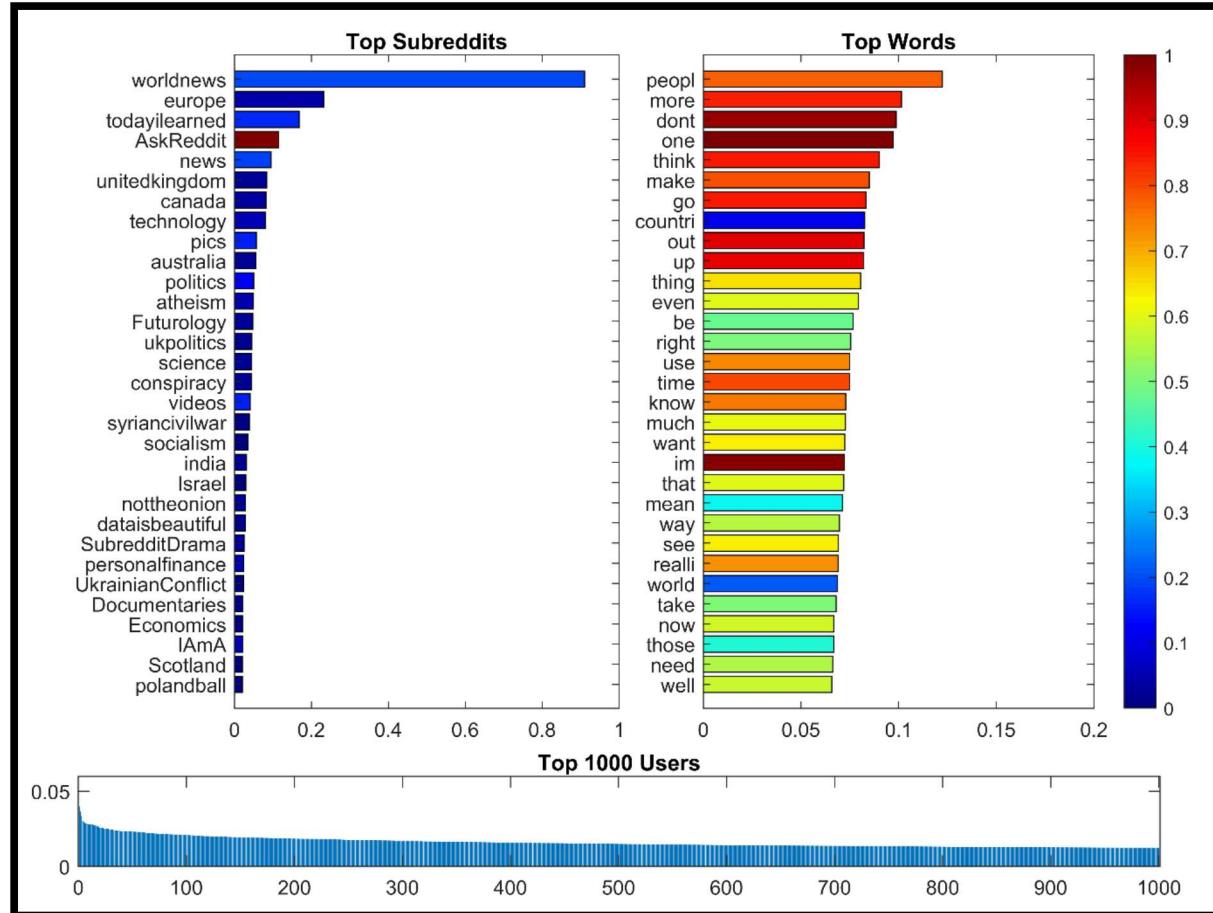
$$\sum_{j=1}^r \mathbf{A}_1(i_1, j) \dots \mathbf{A}_3(i_3, j)$$



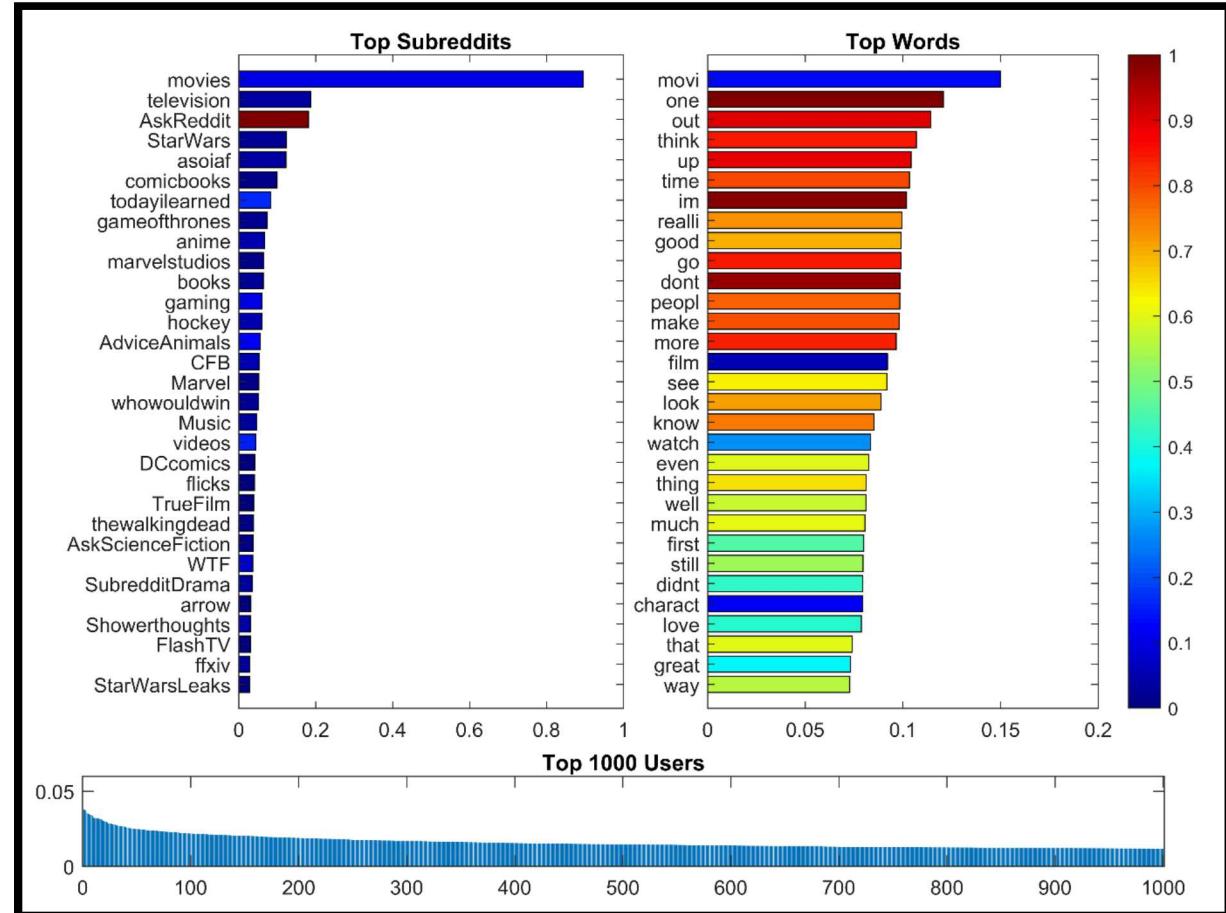
Example Reddit Components Include Rare Words Apropos to High-Scoring Subreddits



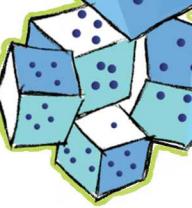
Component #6: International News



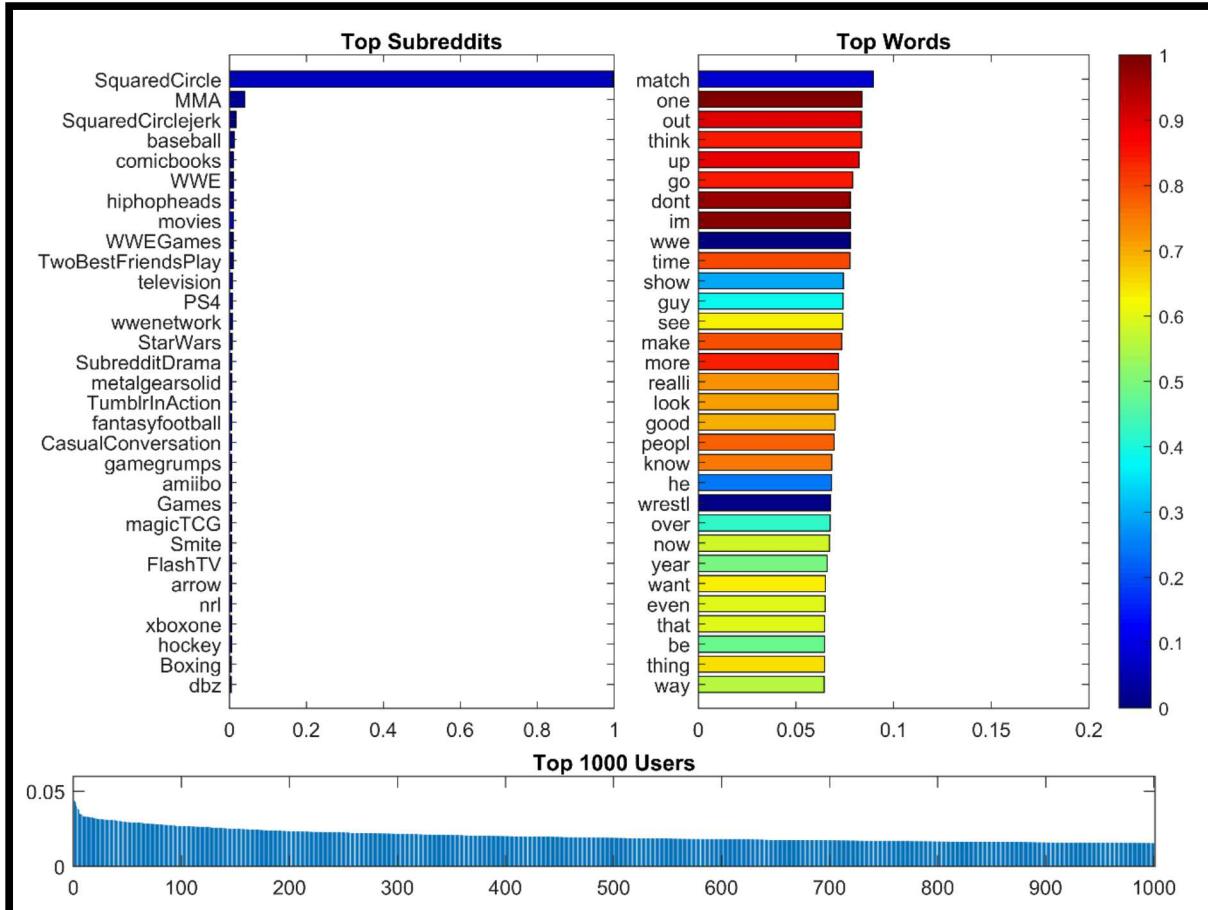
Component #19: Movies & TV



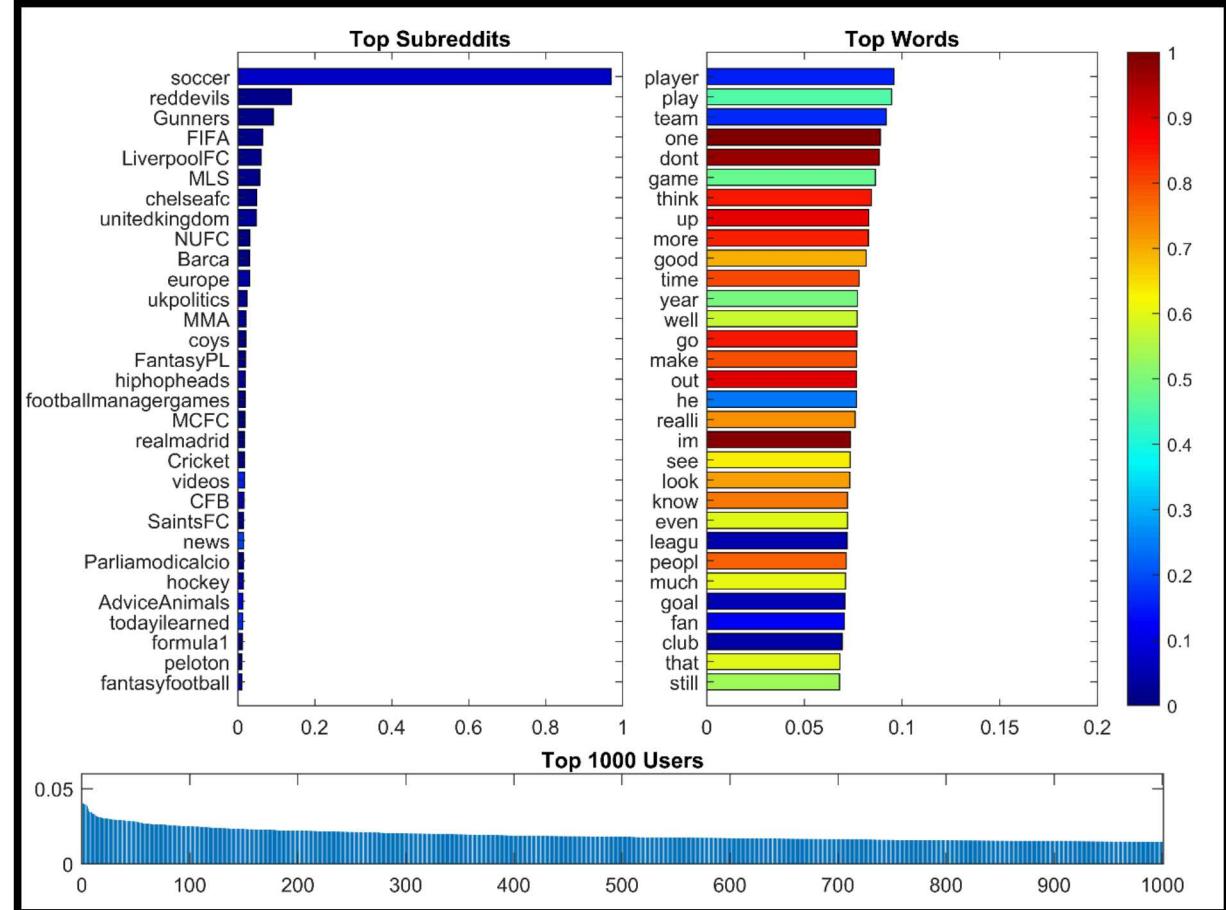
Example Reddit Components Include Rare Words Apropos to High-Scoring Subreddits



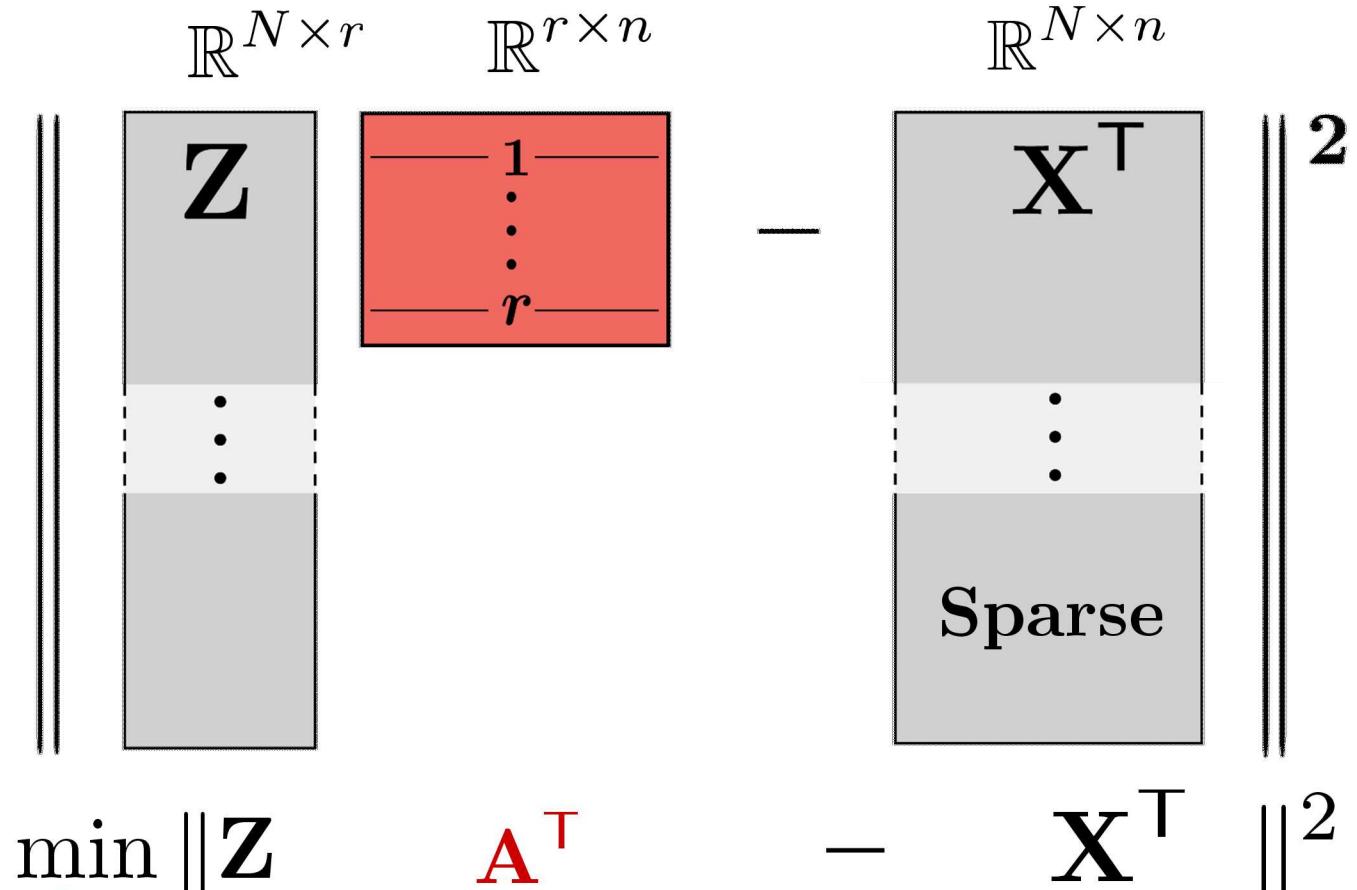
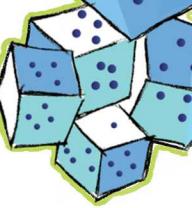
Component #15: Wrestling



Component #18: Soccer



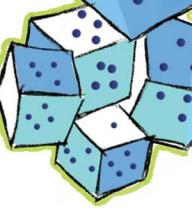
Prototypical CP Least Squares Problem has Khatri-Rao Product (KRP) Structure



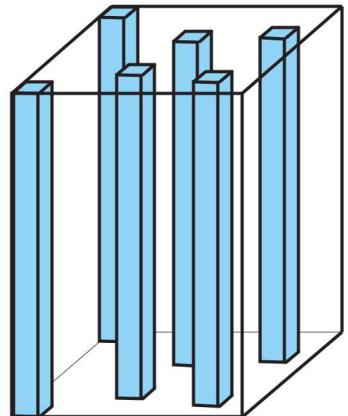
Alternate between
factor matrices.

- Subproblem for CP-ALS
 - Solve $d + 1$ such subproblems per outer iteration
 - Size n = one of the tensor dimensions
- Matrix Z (from the “other” factor matrices)
 - Khatri-Rao product (KRP) of d factor matrices
 - $N = O(n^d)$, i.e. very large
 - Structure of this matrix is key!
- Matrix X^T (from the data tensor)
 - Transpose of mode-unfolding of tensor
 - Sparse if tensor is sparse, including all-zero rows
 - Cannot afford any transform that destroys sparsity
- Matrix A^T (transpose of factor matrix)

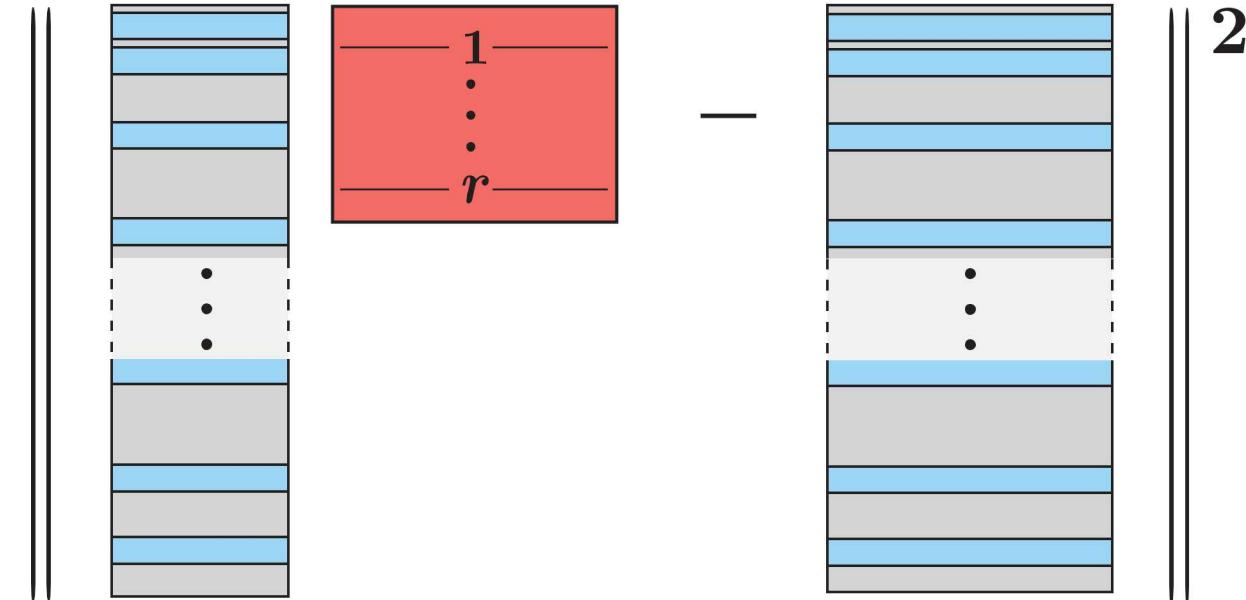
CP-ARLS Leverages Sketching to CP Least Squares Problem



How can we utilize sketching in the inner least squares problem of CP-ALS?



Corresponds to sampling fibers from the tensor

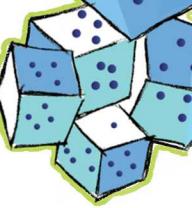
$$\min_{\mathbf{A}} \|\mathbf{S} \mathbf{Z}^{\top} \mathbf{A}^{\top} - \mathbf{S} \mathbf{X}^{\top} \|^2$$


Battaglino, Balladrd, and Kolda (2017). "A Practical Randomized CP Tensor Decomposition"

Ingredient #1: Leverage Scores Key to Limiting Samples (But too Expensive to Compute)



Sandia
National
Laboratories



Leverage score: $\mathbf{Z} \in \mathbb{R}^{N \times r}$

“Economy” SVD:

$$\mathbf{Z} = \mathbf{U} \mathbf{\Sigma} \mathbf{V}^T$$

↑
Spans column space of \mathbf{Z}

Leverage score of row i :

$$\ell_i(\mathbf{Z}) = \|\mathbf{U}(i, :) \mathbf{\Sigma} \mathbf{V}^T\|_2^2 \in [0, 1]$$

Leverage scores indicate which rows most influence solution but cost $O(Nr^2)$ to compute

Rough Intuition:

$$\ell_1(\mathbf{Z}) = 1$$

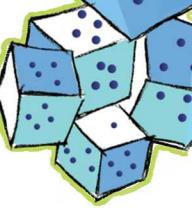
$$\sum \ell_i(\mathbf{Z}) = r$$

How “important” a row is to column space.

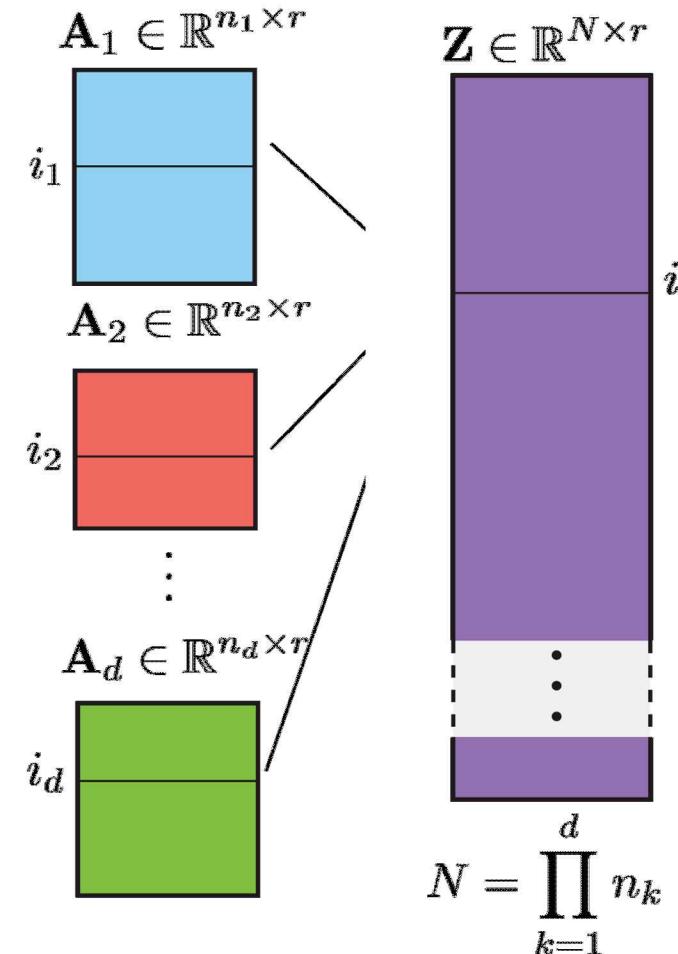
Can use approximate leverage score, pay penalty in required sample number

$$\begin{matrix} z_{11} & z_{12} & \cdots & z_{1r} \\ 0 & z_{22} & \cdots & z_{2r} \\ 0 & z_{32} & \cdots & z_{3r} \\ \vdots & \vdots & \ddots & \vdots \\ 0 & z_{N2} & \cdots & z_{Nr} \end{matrix} = \begin{bmatrix} \nu_1 \\ \nu_2 \\ \nu_3 \\ \vdots \\ \vdots \\ \vdots \\ \nu_N \end{bmatrix}$$

Ingredient #2: Exploit KRP Structure to Bound Leverage Scores



$$\mathbf{Z} = \mathbf{A}_d \odot \cdots \odot \mathbf{A}_1$$



Upper Bound on Leverage Score

Lemma (Cheng et al., NIPS 2016; Battaglino et al., SIMAX 2018):

$$\ell_i(\mathbf{Z}) \leq \prod_{k=1}^d \ell_{i_k}(\mathbf{A}_k)$$

Too expensive to calculate $O(Nr^2)$

Cheap to calculate individual leverage scores $O(r^2 \sum_k n_k)$

Set probability of sampling row i to:

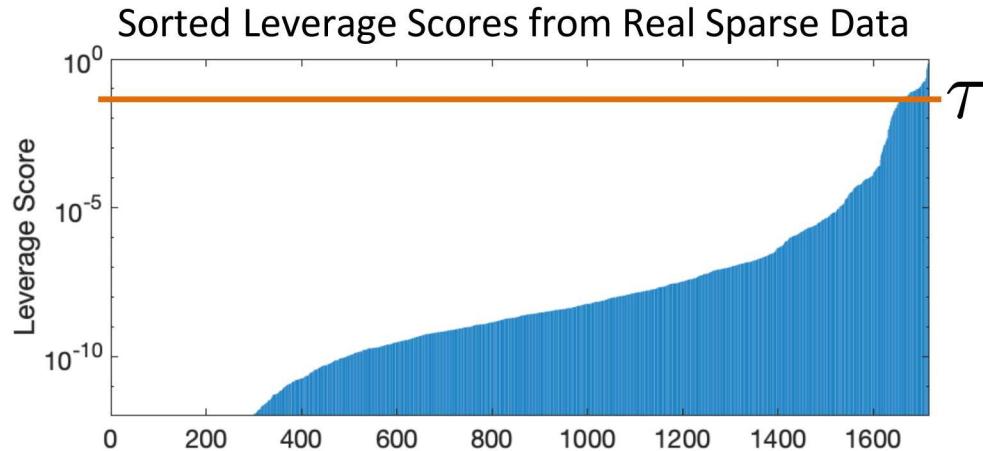
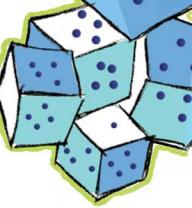
$$p_i \equiv \frac{1}{r^d} \prod_{k=1}^d \ell_{i_k}(\mathbf{A}_k)$$

Sample row from each factor matrix to avoid forming all N possible combinations corresponding to rows of \mathbf{Z} !

1-1 Correspondence between *linear index* and *multi index*:

$$i \in [N] \Leftrightarrow (i_1, \dots, i_d) \in [n_1] \otimes \cdots \otimes [n_d]$$

Ingredient #3: Deterministically Include All High-Probability Rows

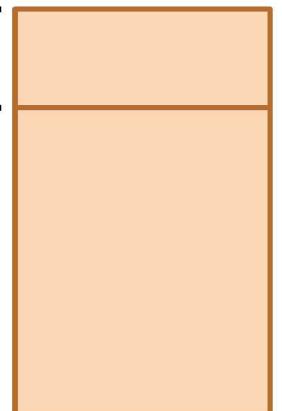


Deterministic Rows

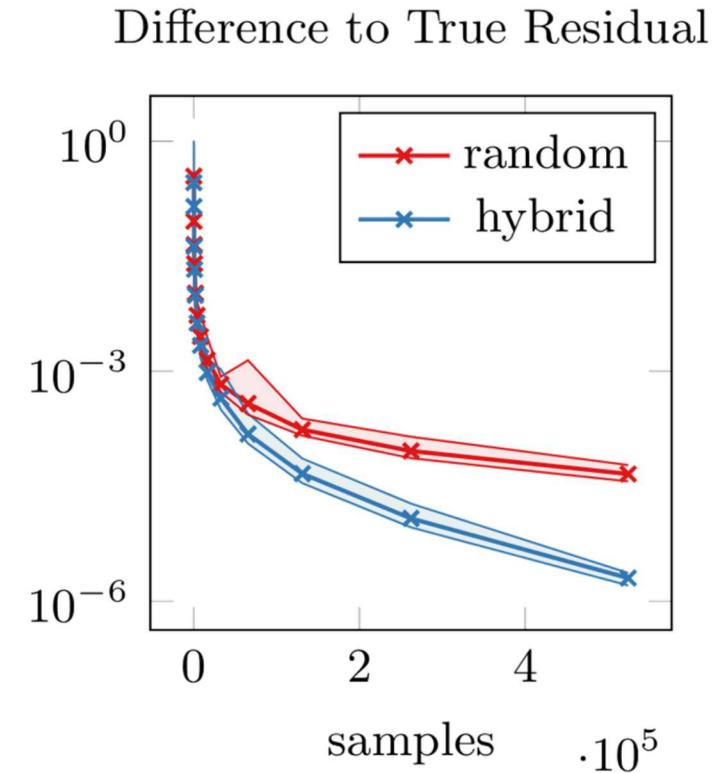
Above τ

$$\mathbf{S}\mathbf{Z} \in \mathbb{R}^{s \times r}$$

Hybrid Sampling:
Combine deterministic
and random rows

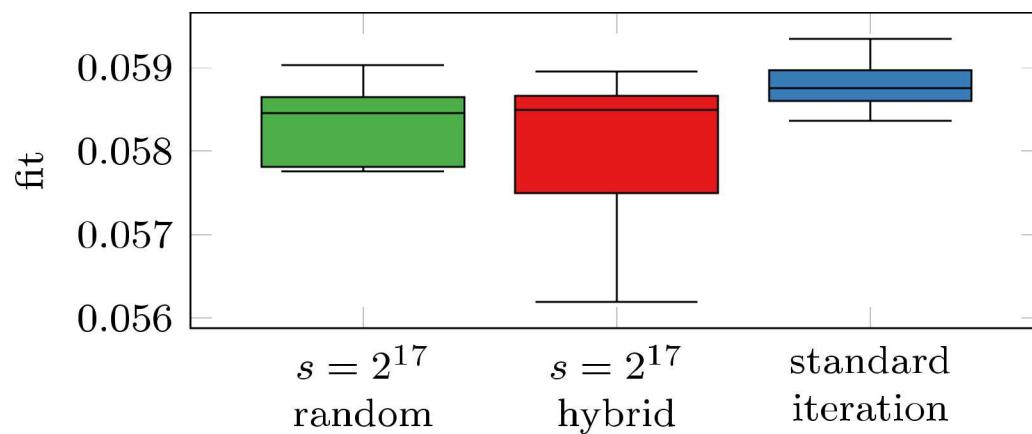
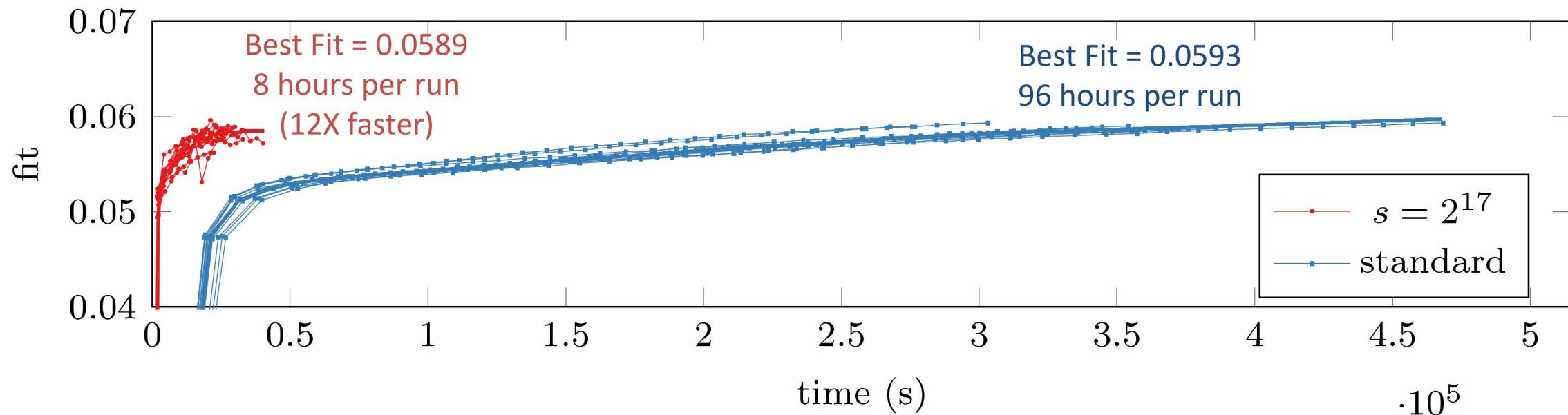
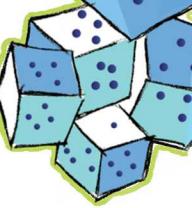


$$s_{rnd} = s - s_{det}$$



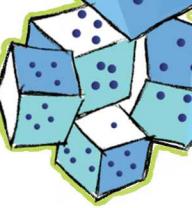
Single Least Squares Problem with
 $N = 46M$ rows, $r = 10$ columns,
 $n = 183$ right-hand sides

Numerical Results on Reddit Tensor

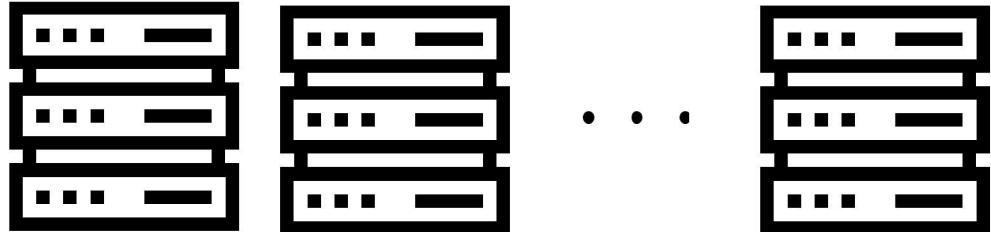


# Samples (S)	Speedup
2^{17} Random	16.08
2^{17} Hybrid	11.87
CP-ALS	1.00

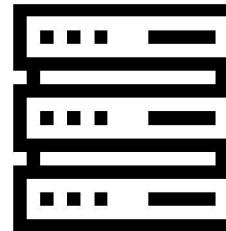
Extensions to Distributed Data and Summary



Large Tensor Stored Across Multiple Nodes



Node with All Factor Matrices

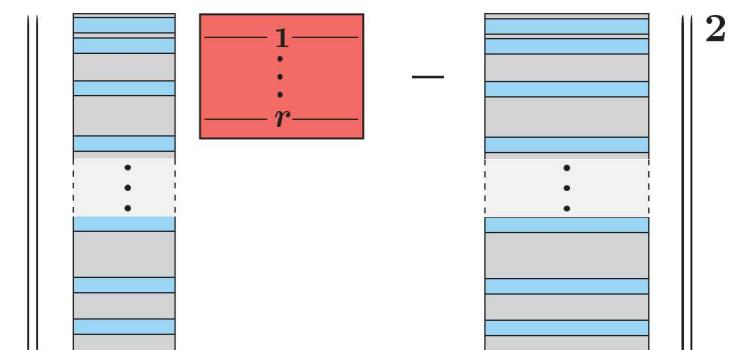


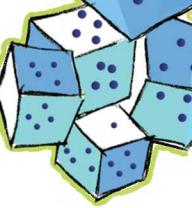
Solve smaller sampled problem on single node

Retrieve sampled fibers from distributed nodes

Summary: Sketching for Sparse Tensor Problems

1. Sampling by leverage scores minimizes required samples
2. KRP structure enables efficient leverage score estimates
3. Hybrid sampling for concentrated leverage scores





Questions

B.W. Larsen and T.G. Kolda. *“Practical Leverage-Based Sampling for Low-Rank Tensor Decomposition”* on arXiv.